LITERATURE SURVEY :

Forecasting Renewable Energy Generation withMachine Learning and Deep Learning: Current Advances and Future Prospects - Natei Ermias Benti , Mesfin Diro Chaka and Addisu Gezahegn Semie

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[1] PAPER 1 : The literature on renewable energy forecasting underscores the increasing reliance on machine learning (ML) and deep learning (DL) techniques to enhance the accuracy of predictions in solar and wind energy generation. Traditional forecasting methods, including statistical models such as Autoregressive Integrated Moving Average (ARIMA) and Numerical Weather Prediction (NWP), have long been employed to estimate energy production. However, these models exhibit limitations in capturing the inherent variability and nonlinearity of renewable energy sources, often resulting in suboptimal accuracy.

Consequently, ML-based approaches have gained prominence due to their ability to learn complex patterns from large datasets. Among supervised learning techniques, Support Vector Machines (SVM), Decision Trees (DT), Random Forest (RF), and Artificial Neural Networks (ANN) have been widely utilized for renewable energy prediction, leveraging meteorological variables such as temperature, humidity, wind speed, and solar radiation. These models excel at recognizing patterns within historical energy generation data, enabling them to produce reliable forecasts. However, they often struggle with handling long-term dependencies and intricate spatial-temporal correlations in renewable energy data, prompting researchers to explore more sophisticated DL architectures.

Convolutional Neural Networks (CNNs) have been employed for spatial pattern recognition in solar and wind energy datasets, while Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) networks have demonstrated superior performance in capturing sequential dependencies and time-series fluctuations in energy production. Hybrid models that integrate CNNs with LSTMs have emerged as particularly effective solutions, as they combine the spatial feature extraction capabilities of CNNs with the sequential learning strength of LSTMs. Furthermore, Reinforcement Learning (RL) has been applied in optimizing real-time energy management, where RL agents learn to balance energy supply and demand dynamically, improving the efficiency of smart grids and energy distribution networks. Despite these advancements, several critical challenges remain.

One major limitation is the dependency on high-quality, high-resolution datasets, which are often unavailable or incomplete due to sensor failures or data collection inconsistencies. The computational expense of deep learning models is another concern, as training large-scale DL models requires substantial processing power, which may not always be feasible for energy providers with limited resources. Additionally, the black-box nature of many ML and DL models raises concerns regarding interpretability, as energy sector stakeholders require transparent and explainable forecasting models to make informed operational decisions.

To address these issues, future research should focus on developing interpretable DL architectures, improving data preprocessing techniques to handle missing and noisy data, and exploring transfer learning strategies to leverage pre-trained models in regions with limited historical data. The integration of physics-informed ML models, which incorporate domain knowledge and physical constraints into learning algorithms, also holds promise for enhancing the reliability of renewable energy forecasting. Ultimately, the continued evolution of ML and DL methodologies, combined with advancements in data acquisition and computational efficiency, will play a pivotal role in enabling more accurate, scalable, and reliable forecasting models, facilitating the seamless integration of renewable energy sources into modern power grids.

A renewable energy forecasting and control approach to secured edge-level efficiency in a distributed micro-grid
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[2] PAPER 2 : The literature on renewable energy forecasting and control in distributed micro-grids emphasizes the increasing role of machine learning (ML) and deep learning (DL) in optimizing energy management, efficiency, and sustainability. Traditional renewable energy forecasting models primarily relied on statistical techniques such as Autoregressive Integrated Moving Average (ARIMA) and Numerical Weather Prediction (NWP). However, these approaches often failed to account for the nonlinear and dynamic nature of renewable energy sources such as solar and wind energy. In response, recent research has adopted ML and DL methodologies, including Artificial Neural Networks (ANN), Support Vector Machines (SVM), Decision Trees (DT), and Random Forest (RF), which have demonstrated superior performance in modeling complex energy systems. More advanced techniques such as Deep Neural Networks (DNN), Convolutional Neural Networks (CNN), and Recurrent Neural Networks (RNN), including Long Short-Term Memory (LSTM) networks, have been particularly effective in forecasting energy demand and supply in real time. However, LSTMs require significant computational resources, which limit their application in resource-constrained environments such as mobile and edge computing devices. To address these limitations, the research in this paper proposes an energy forecasting approach using DNN models on mobile edge devices, reducing latency and communication overhead while ensuring high forecasting accuracy. The study also introduces an innovative electrical network topology for the seamless integration of multiple Renewable Energy Sources (RESs) into a Distributed Renewable Energy Source (D-RES) network. The control mechanism employs a wireless sensor network (WSN) to collect real-time energy data, which is then processed locally on mobile devices to administer efficient grid control with minimal delay. Unlike previous methods that rely on meteorological data for energy prediction, this approach leverages historical power generation data, ensuring reliability even in regions with limited access to weather-based datasets. The forecasting model is trained using a dataset from a solar power company in Belgium, with experiments conducted on varying DNN architectures to determine the optimal layer configurations. The results indicate that increasing the number of hidden layers enhances forecasting accuracy, with the best-performing model achieving a minimal Mean Square Error (MSE) and high R-squared value. Despite these advancements, challenges such as computational constraints on mobile devices, model interpretability, and data availability remain critical concerns. Future research should focus on improving energy-efficient DNN models, exploring transfer learning to adapt models across different micro-grid environments, and integrating physics-informed neural networks to enhance the robustness of forecasting systems. By addressing these challenges, ML and DL-driven forecasting solutions will continue to play a crucial role in the evolution of smart and sustainable energy grids.

Advancing Renewable Energy Forecasting: A Comprehensive Review of Renewable Energy Forecasting Methods

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[3] paper 3: The literature survey in the uploaded document explores various forecasting models and methodologies in the domain of renewable energy, particularly focusing on photovoltaic (PV) and wind power generation. The review classifies forecasting models into four main types: physical models, statistical models, artificial intelligence-based methods, and hybrid models. Physical models rely on meteorological parameters such as solar radiation and wind speed, incorporating numerical weather prediction (NWP) but suffering from high computational costs and inefficiencies in short-term forecasting. Statistical models, on the other hand, utilize historical data to establish patterns and trends but struggle with non-linear and irregular data, necessitating extensive pre-processing. The emergence of artificial intelligence (AI)-driven models, including artificial neural networks (ANNs), support vector machines (SVMs), and deep learning architectures, has significantly enhanced forecasting accuracy by capturing complex non-linear relationships within energy datasets. However, these AI models often encounter challenges such as overfitting, high computational demands, and sensitivity to data quality. To address these limitations, hybrid models integrate multiple forecasting techniques, combining the strengths of individual approaches to improve accuracy and robustness. The review further discusses the importance of selecting appropriate forecast horizons—short-term, medium-term, and long-term—based on the specific application, with short-term forecasts being crucial for grid stability and long-term predictions aiding in strategic planning. The document highlights that machine learning-based approaches, particularly deep learning and ensemble methods, are increasingly being adopted due to their superior performance. However, their success depends on factors such as data availability, computational efficiency, and integration with optimization techniques. Additionally, transfer learning has been identified as a promising avenue for enhancing forecasting accuracy by leveraging knowledge from pre-trained models applied in related domains. Future research directions emphasize the need for improved data integration, enhanced computational efficiency, and real-time adaptability in forecasting models to support the growing reliance on renewable energy sources